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Study of Ant Colony Algorithm using Adaptive Schematization Methodology Based on Prognosticative Learning

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***Abstract*— To solve the path schematization in the complicated environments, a new adaptive schematization methodology using ant colony algorithm (AACA) based on prognosticative learning is presented. A novel prognosticative operator for direction during the ant colony state transition is constructed based on an obstacle restriction method (ORM), and the prognosticative results of proposed operator are taken as the prior knowledge for the learning of the initial ant pheromone, which improves the optimization efficiency of ant colony algorithm (ACA). To further solve the stagnation problem and improve the searching ability of ACA, the ant colony pheromone is adaptively adjusted under the limitation of pheromone. Compared with the corresponding ant colony algorithms, the simulation results indicate that the proposed algorithm is characterized by the good convergence performance on pheromone during the path schematization. Furthermore, the length of planned path by AACA is shorter and the convergence speed is quicker.**

***Keywords-** Ant colony algorithm; Artificial intelligence ; Adaptive behaviour; Combinatorial optimization; Reinforcement learning; Path Schematization; Robotics;Prognosticative Learning; Adaptive Adjustment(key words)*

I. INTRODUCTION

Path schematization is one of key technologies in the autonomous navigation for mobile robot. It refers to searching an optimal or approximate optimal and collision-free path from the starting point to the goal according to certain optimization criterion (e.g., minimal working cost, shortest walking route) in the complicated environments. The path schematization for mobile robot is a kind of typical NP-Hard problem. The common methods include artificial potential field (APF) method, visibility graphs, free-space method, topological method, and so on. The APF method is used widely for its simple model, good real-time property and easy realization, however, it has some deficiencies in easily trapping into local minimum, swaying in cabined route way, etc. The traditional schematization methods have some deficiencies in global optimization and robustness, etc. In recent years, along with the development of artificial intelligent, some new intelligent algorithms have got considerable development, and show good flexibility, robustness and global optimization ability, such as fuzzy logical, neural network, genetic algorithm (GA), artificial immune algorithm and so on. To some extent, the fuzzy logical overcomes the local minimum, however, it has the disadvantage in the incompleteness of experiences and the fuzzy reasoning table will rapidly expand with the increase of input quantity. In the neural network technology for the path schematization, the awareness space of mobile robot is mapped into behavior space. To realize the path schematization, the data from sensors are taken as input of network, and the expected moving direction is taken as output. However, it is very difficult to get the sample data which distribute in the whole working space of robot. In the genetic algorithm for path schematization, the environment around robot is coded from the starting point to the goal, and the optimal path is achieved through continuous optimization using the selection, crossover, mutation operator, which is characterized by the global optimization ability and robust. However, the genetic algorithm has the deficiencies in the large searching space, complicated coding and large calculation, and so on. Inspired by the biology immune system, the artificial immune system develops a new approach for the path schematization for its properties of self-organization, self-learning and immunological memory. Xiao et al. realized the path schematization based on immune genetic algorithm through crossover, mutation and vaccine inoculation operator.

However, the deficiencies in the GA still exist in the immune genetic algorithm. Meshref et al. solved the dog and sheep problem in the distributed autonomous robotics system based on Farmer's dynamic model, however, the method is short of global optimization ability. Inspired by the mechanism of Jerne's idiotypic network hypothesis, Zhuan et al. converted the path schematization into space search in the antibody network using the stimulation and suppression between the antigen and antibody, and provided a new immune network algorithm (INA), Experimental results show that the INA is characterized by good quickness and flexibility, however, the searching precision and convergence property of INA need further improvement. From the development of path schematization, much attention has been focused on the bionic artificial intelligence algorithms. Ant colony algorithm (ACA) is a kind of optimization algorithms for the graph search and is characterized by the positive

feedback, parallel computing and strong robustness, which is inspired by the mechanism of ant
finding foods in nature. At present, ACA is successfully used in the digital image processing, data mining, pattern recognition, especially path schematization for the mobile robots. Referencing the idea of artificial potential field method, Sun et al. constructed an attraction probability function whose weight can be adjusted and the function was taken as heuristic factor, which quickened the convergence speed of ACA, and also made the ACA easily trap into the local minimum. Based on the environment built using free-space method, Tan et al. finished the graph search using ACA. However, the characteristic information extraction of environments is a complex course. Gao et al. presented an augment ant colony algorithm to improve the searching efficiency of path schematization. At present, the initial pheromone of ACA is equal and constant. With the improvement of complexity of path schematization, unreasonable initial pheromone will increase the computation time and make the ACA trap into the local minimum. To improve the global schematization efficiency of ACA, a prognosticative operator for direction is constructed in this paper. The schematization results of prognosticative operator are taken as the prior knowledge and the initial pheromone is learnt using the knowledge. Furthermore, the evaporation coefficient of pheromone is adaptively adjusted, which improves the schematization efficiency and precision of ACA well.

II. ANT COLONY ALGORITHM

Inspired by the behavior of colonies of real ants, ant colony optimization algorithm was first proposed in the early 1990s by Marco Dorigo. It is known that each ant leaves the information on the path it has traversed by depositing a chemical substance called pheromone on the ground. Ants have a tendency to follow these pheromone trails. Within a fixed period, shorter paths between nest and food can be traversed more often than longer paths, and so they obtain a higher amount of pheromone, which, in turn, tempts a larger number of ants to choose them and thereby to reinforce them again. The behavior of ant colony is shown in Fig. 1.

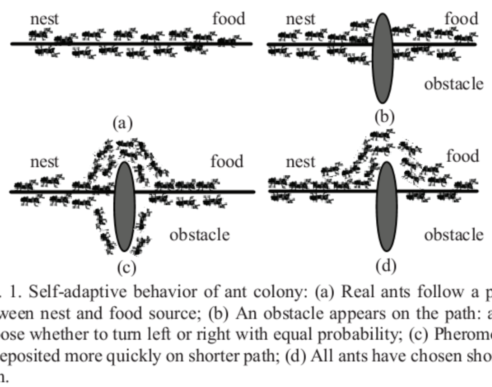

Fig. 1. Self-adaptive behavior of ant colony: (a) Real ants follow a path between nest and food source; (b) An obstacle appears on the path: ants choose whether to turn left or right with equal probability; (c) Pheromone is deposited more quickly on shorter path; (d) All ants have chosen shorter path.

III. CONSTRUCTION OF PROGNOSTICATIVE OPERATOR FOR DIRECTION AND LEARNING OF INITIAL PHEROMONE

To improve the decision ability to environment in the mobile robot autonomous navigation, an obstacle-restriction method (ORM) was presented. The expected direction for the mobile robots can be predicated using the ORM through determining the zones of goal and obstacles. In this paper, a prognosticative operator for direction is constructed and the initial pheromone is learnt based on Minguez's ORM, which improves the searching efficiency of ACA in the path schematization. To corporate the construction of prognosticative operator, a virtual robot (ant) as shown in Fig.2 is provided. The robot is evenly equipped with eight virtual sensors and the detection direction is 1~8.

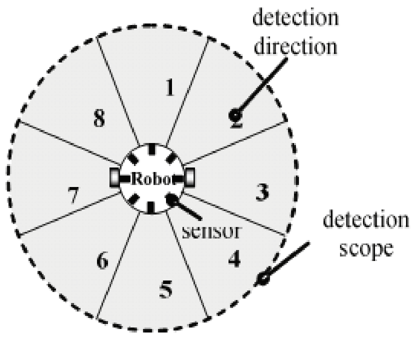

Fig.2 Virtual mobile robot

The construction of prognosticative operator includes the following three steps.

Step 1 Determine the goal zone Z_{goal}.

Let θ_{goal} be the angle zone of goal P_{goal} at the detection direction of mobile robot. According to the principle of goal
tendency, the goal zone can be defined as follows:

$$\angle Z_{goal} = \theta_{goal} \qquad (1)$$

The goal zone is constructed as shown in Fig.3(a).

Step 2 Determine the obstacle zone Z_{obs}. The determination of obstacle zone is based on single Obstacle or multiple adjacent obstacles. Multiple detached obstacles can be overlapped on the above model. Let θ_{obs} be the angle zone of obstacle P_{obs} at the detection direction (See Fig.3 (b)). Firstly, the dangerous zone is defined as follows.

$$Z_{danger} = \bigcup_{i \in n} \theta_{obsi} \qquad (2)$$

Where, n is the number of detection zone of robot. The detection angle of dangerous zone is θ_d. Considering the allowable shortest distance between the robot and obstacle, the safe zone is defined as follows.

$$Z_{safety} = \begin{cases} Z_{s\_L} = [\max(\theta_d), \max(\theta_d) + \frac{2\pi}{n}] \\ Z_{s\_R} = [\min(\theta_d), \min(\theta_d) - \frac{2\pi}{n}] \end{cases} \quad (3)$$

Where, Z_{s_R}, Z_{s_L} are the left and right zone of dangerous
zone respectively as shown in Fig.3(c).
The obstacle zone (See Fig.3(d)) is defined as follows.

$$Z_{obs} = Z_{danger} \bigcup Z_{safety} \quad 4$$

Let θ_{Tobs} be the direction angle of obstacle zone.

Step 3 Determine the prognosticative zone. According to Z_{goal} and Z_{obs}, the prognosticative zone is given by

$$Z_{\exp} = Z_{goal} \bigcap Z_{obs} \quad 5$$

If $Z_{exp} = \Phi$, there is no any superposition between the goal and obstacle zone (See Fig.3(e)), and the expected direction θ_{exp} is the same as the goal direction, i.e.

$$\theta_{\exp} = \theta_{goal} \quad 6$$

If $Z_{exp} \neq \Phi$, there is superposition between the goal and obstacle zone (See Fig.3(f)), the exp is defined as follows.

$$\theta_{\exp} = \begin{cases} \max(\theta_{Tobs}) + \frac{\pi}{n} & if\ |\theta_{goal} - \min(\theta_{Tobs})| \geq |\theta_{goal} - \max(\theta_{Tobs})| \\ \min(\theta_{Tobs}) - \frac{\pi}{n} & if\ |\theta_{goal} - \min(\theta_{Tobs})| < |\theta_{goal} - \max(\theta_{Tobs})| \end{cases} \quad 7$$

Since the expected direction angle θ_{exp} is a zone, to facilitate the learning of initial pheromone of ACA, let $\bar{\theta}_{exp}$ be the central anger of expected direction angle. If there is no any prior knowledge, the initial pheromone of ACA is ή =1/N (N is the number of grid around the ant), i.e. the concentration of pheromone between the ant and each adjacent grid is equal. In this paper, the schematization result of direction prognosticative operator is taken as the prior knowledge and the initial pheromone of ACA is optimized. The concrete operating sequences are as follows:

Step 1 Confirm that the ant reaches the grid firstly.

Step 2 Calculate the central anger $\bar{\theta}_{exp}$ based on the direction prognosticative operator.

Step 3 Calculate the anger between the $\bar{\theta}_{exp}$ and moving directions to the eight adjacent grids around ant.

Step 4 The grid with minimal angle is given the maximal pheromone, then grid is taken as center, and other grids are given the pheromone symmetrically with equal weights. In this paper, for the transition direction of ant is selected using a roulette-wheel algorithm, the grid with maximal pheromone will be selected with great probability and the grid is just the expected direction of ants, which will improve the transition speed of ants. In addition, the grid with minimal pheromone has the possibility to be selected too, which guarantees the rationality and diversity. In our experiment, according to the increasing sequence of angles, the initial pheromone of eight grids is given {0.4, 0.19, 0.19, 0.07, 0.07, 0.03, 0.03, 0.02} respectively.

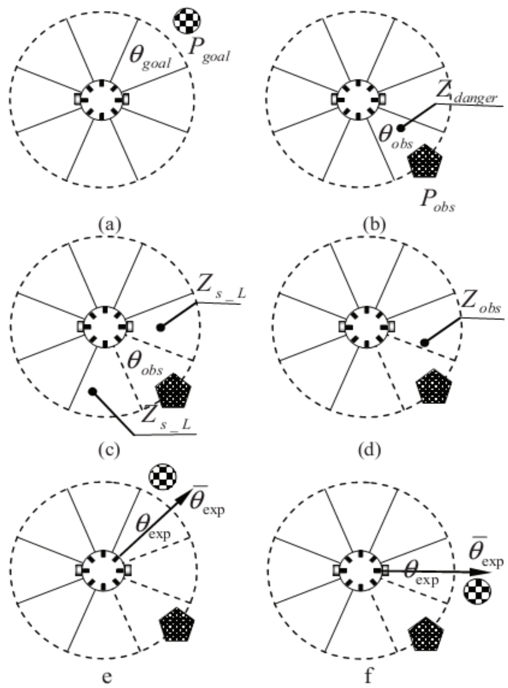

Fig. 3. Construction process of predictive operator

IV. ADAPTIVE ACA BASED ON PROGNOSTICATIVE LEARNING

Problem Description and Model Building

According to the principle of path schematization based on ACA, the path schematization can be described using a directed graph G=(V, E, f), where V is the set of nodes of graph, E is the set of edges connecting the nodes in the graph, f is the objective function of feasible solutions to path schematization, namely the collision free and shortest path. The artificial ant is placed in the graph G, and the graph is searched through the state transition of ants. Environment modeling is the key link of robot path schematization and is the mapping from the physical space to abstract space where the algorithm is carried out. The schematization results are usually embodied through the environmental model. At present, there are two kinds of modeling methods, one is geometric method, namely the environmental information is collected through the perception sensors installed in the robot, the abstract geometric characteristics are extracted from the information, the free position space is mapped to the weighted graph, and the path schematization is converted to the graph search; the other is grid method, namely the whole schematization environment is divided into several grids with the same size, the data structure of grid is the pixel array, and each pixel has its position determined by the row and column. In this paper, the grid method is adopted to divide the environment information, the data is coded using direct coding and the environment is expressed using the graph theory thought which is from the geometric method. Let WS be a limited two-dimensional (2-D) workspace in polygonal shape, where there exist some static obstacles Obs_i (i=1,2,…,n). To avoid the robot too close to the obstacles, the boundaries of obstacles are expanded to some extent according to the cross section of robot and minimum distance between the robot and obstacle, and the robot is presented by a point. In the WS, the rectangular coordinate system Σ_0 is built. The maximum of WS at the directions X and Y are x_{max} and y_{max} respectively. Fig.4 shows the grid series with 10x10, where the black squares denote the obstacles.

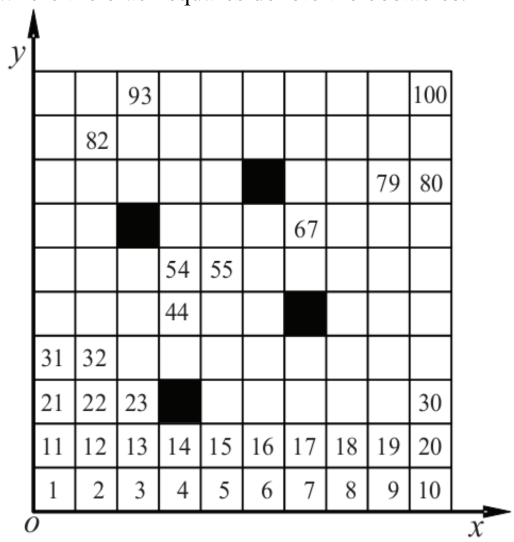

Fig. 4. Grid coordinate and series

Let δ be the step size of mobile robot. The whole schematization zone is divided according to the step size. The number of grid in each row is $N_x = (x_{max})/(\delta)$, and the number in each column is $N_y = (y_{max})/(\delta)$. Let g be the any grid and G be the set of all grids in the WS space, the determinate coordinate of $g \in G$ in the WS space is (x,y). Let N={1,2,3….,M} be the set of grid series number, there exist the following mapping relationship between the series number $i \in N$ and coordinate (x_i,y_i) of g_i.

$$\begin{cases} x_i = ((i-1) \mod N_x) + N_x/2 \\ y_i = \mathrm{int}((i-1) / N_x) + N_y/2 \end{cases} \quad 8$$

Where, mod and int are the remain and round function respectively.

Algorithm Flow

Step 1 Initialize parameters: the maximum cycle times T_{max}, ant number K, tabu list $Tabu_k$ k=1,2,…N, the number of initial grid and final grid, and other parameters. $t \leftarrow 0$, $k \leftarrow 0$.

Step 2 Cycle times: $t \leftarrow t+1$.

Step 3 Put the ant k at the initial grid: $k \leftarrow k+1$, and the initial grid is placed in the tabu list $Tabu_k$.

Step 4 Judge whether the current grid is the grid that the ant arrived firstly. If so, the initial pheromone of the grid is learnt based on the prognosticative operator, or go to step 5.

Step 5 Transfer ant k. To realize the reasonable transfer of ant k from grid i to j , the pseudo-random-proportional rule is adopted in this paper. When ant k locates in grid i , the transfer function for ant to transfer to the next grid j is given as follows:

$$j = \begin{cases} \underset{l \in allowed_k}{\arg\max} \{[\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}(t)]^{\beta}\}, & if\ q \le q_0 \\ j' & if\ q > q_0 \end{cases} \quad 9$$

Where, q is a value chosen randomly with uniform probability in [0, 1], q_0 $0 \le q_0 \le 1$ is a parameter such that the higher q_0 the smaller the probability to make a random choice, and variable j' is determined according to the following equation:

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}(t)]^{\beta}}{\sum_{l \in allowed_k} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}(t)]^{\beta}} & j \in allowed_k \\ 0 & j \notin allowed_k \end{cases}$$

10

Where $p_{ij}^{k}(t)$ denotes the transfer probability of ant k from grid i to j at time t, α is the pheromone enlightening factor, β is the goal enlightening factor, $allowed_k$ is the next allowed grid chosen by ant k, $\tau_{ij}(t)$ is the pheromone from grid i to j at time t, and $\eta_{ij}(t)$ is the goal enlightening function, which is defined as follows:

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad 11$$

$$d_{ij} = d(g_i, g_j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \quad 12$$

Step 6 Judge whether an ant has finished path search. If not, go to Step 4.

Step 7 Judge whether all ants have finished a cycle. If not, go to Step 3, otherwise the pheromone is updated according to equation (13).

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \rho\Delta\tau_{ij} \quad 13$$

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \quad 14$$

Where, ρ is the evaporation factor of pheromone, 1- ρ denotes the remnant factor of pheromone and $\rho \subset [0,1]$. $\Delta\tau_{ij}^{k}$ denotes the remnant pheromone on the path by ant k in this cycle. $\Delta\tau_{ij}$ is the increment of pheromone on the path from grid i to j in this cycle. In this paper, the Ant-cycle model is adopted and defined as follows:

$$\Delta\tau_{ij} = \frac{Q}{L_k} \qquad 15$$

Here, Q is a constant, and L_k is the length of path searched by ant k. Evaporation factor ρ reflects the remains of pheromone as time goes on, which will affect the global searching ability and convergence speed of ACA. If ρ is increased, the pheromone of grid that is rarely passed tends to 0, which affects the randomness of ACA and decreases the global searching ability. If ρ is decreased, the randomness and global searching ability are increased, however, the convergence speed will be decreased. In this paper, the evaporation factor ρ is adaptively changed and is expressed as follows:

$$\rho = \rho_{\min} + t\frac{(\rho_{\max} - \rho_{\min})}{T_{\max}} \qquad 16$$

Where, ρ_{min} and ρ_{max} are the minimal and maximal evaporation factor respectively, and T_{max} is the maximal cycle times.

Step 8 Judge whether the termination conditions are satisfied. If not, go to step 2, otherwise output the optimal path.

In this paper, the termination conditions include: (1) Reach the maximum cycle times; (2) The length of optimal path doesn't change for several generations. To improve the optimization efficiency, the optimum reservation methodology is adopted during the optimization.

V. SIMULATION EXPERIMENT AND ANALYSIS

To verify the validity of adaptive ant colony algorithm (AACA) for path schematization based on the prognosticative learning, aiming at two environments which are divided into 25, some experiments are carried out with MATLAB RC2010 on an Intel Pentium IV 3.1GHz computer with 2GB RAM, and the schematization results are compared with those of simple ant colony algorithm (SACA) and improved ant colony algorithm (IACA). Considering the randomness, each algorithm is independently tested many times. In AACA, K=20, α=1,β=2, ρ_{min}=0.01, ρ_{max}=0.98,Q=0.1. In SACA, K=20, α=1, β=2, ρ=0.85, Q= 0.1. In IACA, K=20, α=2.5, ρ_{min}= 0.5, weight coefficient of attraction enlightening factor K_0=0.15, weight coefficient of turning times K_1= 15. The maximum cycle times of three algorithms are 50. The convergence condition of three algorithms is: The length of optimal path doesn't change for fifteen generations. Fig.5 and Fig.6 are the optimal schematization results in two environments respectively. From the two figures, it can be seen that three ant colony algorithms can find their optimal paths, which shows the self-organization, self-learning of ant colony algorithm.

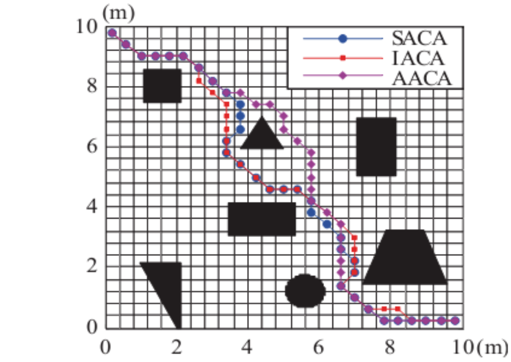

Fig.5 Optimal planning results in Environment I

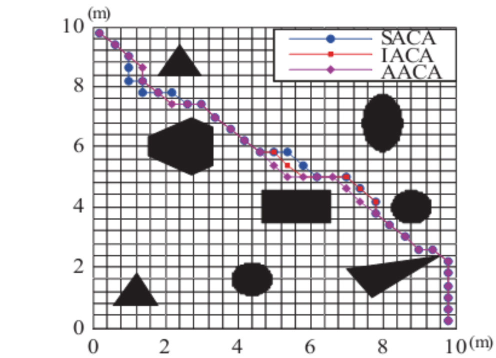

Fig.6 Optimal planning results in Environment II

Table I is the contrast of schematization results of three algorithms in two environments. P1, P2 and P3 are the convergence speed, length of optimal path, length of average path respectively. From the table, it can be seen that the transition efficiency of ant colony is improved for the initial pheromone in proposed AACA is learnt based on the prognosticative operator. Furthermore, the adaptive evaporation factor realizes the early approximate search and later subtle search during the path search, which make the convergence speed of AACA be the quickest, the length of optimal path and average path be the shortest. In addition, the convergence speed of SACA is the slowest, and its schematization ability is the worst. Fig. 7 is the average evolutionary curves of three algorithms in two environments. From the figure, it can be seen that the average evolutionary speed of proposed AACA is the quickest and the optimization ability is the strongest.

Table I. Contrast of planning results among three algorithms.

Algorithm	Environment I			Environment II		
	P1	P2 (m)	P3 (m)	P1	P2 (m)	P3 (m)
SACA	19.45	16.58	18.33	21.78	15.68	16.17
IACA	15.18	16.25	17.26	18.43	15.22	15.56
AACA	13.77	15.92	17.08	12.76	14.98	15.21

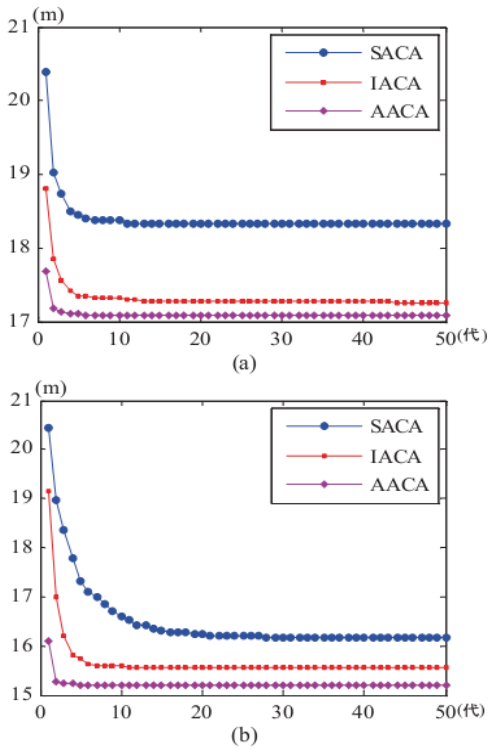

Fig.7 Average evolutionary curves of three algorithms.
(a) Environment I; (b) Environment II

CONCLUSION

To improve the schematization efficiency and precision of ACA, a prognosticative operator for direction based on ORM is presented in this paper. The schematization results of prognosticative operator are taken as the prior knowledge and the initial pheromone is learned. Furthermore, the evaporation factor is adaptively adjusted. The experimental results verify the effectiveness of proposed AACA. In this paper, the prognosticative operator is used to optimize the initial pheromone of ACA and the effective limits of prognosticative operator are the grids which are reached firstly by ants. To use the prognosticative operator effectively, the transfer function for ants can be re-defined through integrating schematization results of prognosticative operator, and the action of prognosticative operator is expanded to the whole period of optimization of ACA, which will be helpful to the further improvement of ACA. How to realize the above improvement of ACA will be our future work.

REFERENCES

[1] Jiafu Tang, Jun Zhang, Zhendong Pan. A scatter search algorithm for solving vehicle routing problem with loading cost, Expert Systems With Applications, vol. 37, pp. 4073-4083,2010.

[2] H.D. Zhang, R. Zheng,Y. W.CEN Yu-wan, Present situation and future development of mobile robot path schematization technology, Journal of System Simulation, Vol.17, No.2:439-443, 2005.

[3] Dorigo, M, Maniezzo, V, Colorni, A. Ant system: Optimization by a colony of cooperating agents, IEEE Transactions on Systems Man and Cybernetics Part B-Cybernetics, vol.26, pp.29-41, 1996.

[4] B. X. Xiao, Y. F.Yu, L. Yu, et al. Mobile robot global path schematization based on immune genetic algorithm, Computer Engineering and Applications, Vol. 43, No. 30, 91-93, 2007.

[5] G. Q. Liu, T. J. Li and Y. P. Li, The ant algorithm for solving robot path schematization problem, Proceedings of the Third International Conference on Information Technology and Applications, 25-27, 2005.

[6] Gambardella. L, Taillard. E, Dorigo, M. Ant Colonies for the QAP, Technical Report, vol. 97-4, 1997.

[7] G. Z. Tan, H. He, A. Sloman, Ant colony system algorithm for real-time globally optimal path schematization of mobile robots, Acta Automatica Sinica,Vol.33, No.3, 279-285,2007.

[8] Yu. B, Yang. ZZ, Yao, BZ. An improved ant colony optimization for vehicle routing problem, European Journal of Operational Research, vol. 196, pp. 171-176, 2009.

[9] Puris, A, Bello, R, Herrera, F. Analysis of the efficacy of a Two-Stage methodology for ant colony optimization: Case of study with TSP and QAP, Expert Systems With Applications, vol. 37, pp. 5443-5453, 2010.

[10] D.Martens, M.D.Backer, R. Haesen, B. Baesens, C. Mues, and J. Vanthienen, “Ant-based approach to the knowledge fusion problem,” in Proc. ANTS 2006, ser. LNCS, M. Dorigo et al., Eds., Springer Verlag, vol. 4150, pp. 84–95, 2006.

[11] H. Alt, E. Wweiz, Visibility graphs and obstacle-avoiding shortest paths, Mathematical Methods of Operations Research, Vol. 32, No. 1 3: 1432-2994, 1988.

[12] J. Zhuang, S. A. Wang. Further study of robot path schematization algorithm based on artificial immune net theory, Journal of System Simulation, Vol. 16, No. 5, 1017-1019, 2004.